
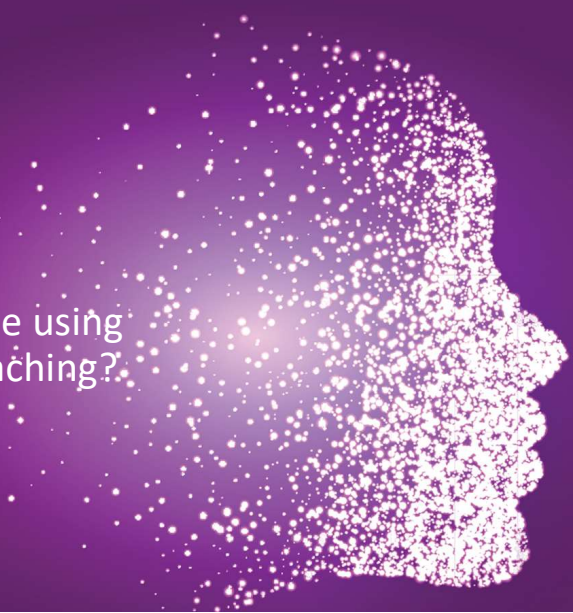


worldusabilityday

Catch me if you can


How to fight Fraud, Waste and Abuse using Machine Learning AND Machine Teaching?

Cupid Chan
2020-11-12




CCSQ WORLD USABILITY DAY 1

1




ODPi
odpi.org


+



DLFAI



DLFAI
& DATA



The dashboard displays a grid of various AI and data-related tools and services, including:

- Machine Learning: Framework, Platform, Library, Tool, Reinforcement Learning, Programming
- DLFAI & DATA: Notebook Environment, Versioning, Store & Format, Operations, Stream Processing, SQL Feature Engine, Visualization, Pipeline Management, Labeling and Annotation, Governance
- Model: Benchmarking, Training, Parameter, Format & Interface, Marketplace, Workflow, Inference, Tool, Explainability, Adversarial, Bias & Fairness
- DLFAI & DATA: Computing & Management, Interface, Security & Privacy, Natural Language Processing, Education

2

The image shows a LinkedIn profile for Jacqueline Mars on the left and a chat window on the right. The profile includes a header with her name and '1st' degree, a profile picture, and a background image. Below the header are sections for 'Highlights' (16 mutual connections), 'Experience' (Co-Founder of AMERICAN CANDY CO LIMITED), and 'Education' (Miss Hall's School). The chat window shows a conversation between Jacqueline Mars and Cupid Chan. Jacqueline Mars asks 'What do you do?' and Cupid Chan responds with details about his work in AI and Analytics. Jacqueline Mars then asks for an exclusive investment opportunity, and Cupid Chan explains the meaning of 'exclusive'.

3

The image shows a chat conversation between Jacqueline Mars and Cupid Chan. Jacqueline Mars asks 'What do you do?' and Cupid Chan responds with details about his work in AI and Analytics. Jacqueline Mars then asks for an exclusive investment opportunity, and Cupid Chan explains the meaning of 'exclusive'.

4

LinkedIn Story to be continued...



5

10 seconds Polling Question

Have you watched the movie “Catch me if you can”?



6



7

How to fight
Fraud, Waste
and Abuse using
Machine
Learning AND
Machine
Teaching?

catch me

if you can

Presented by
Cupid Chan

Human-Centered
Design
Center of Excellence

WORLD USABILITY DAY

8

Fraud, Waste, Abuse and Error



Fraud

Intentional Deception



Abuse

Bending the rules



Waste

Inefficiency



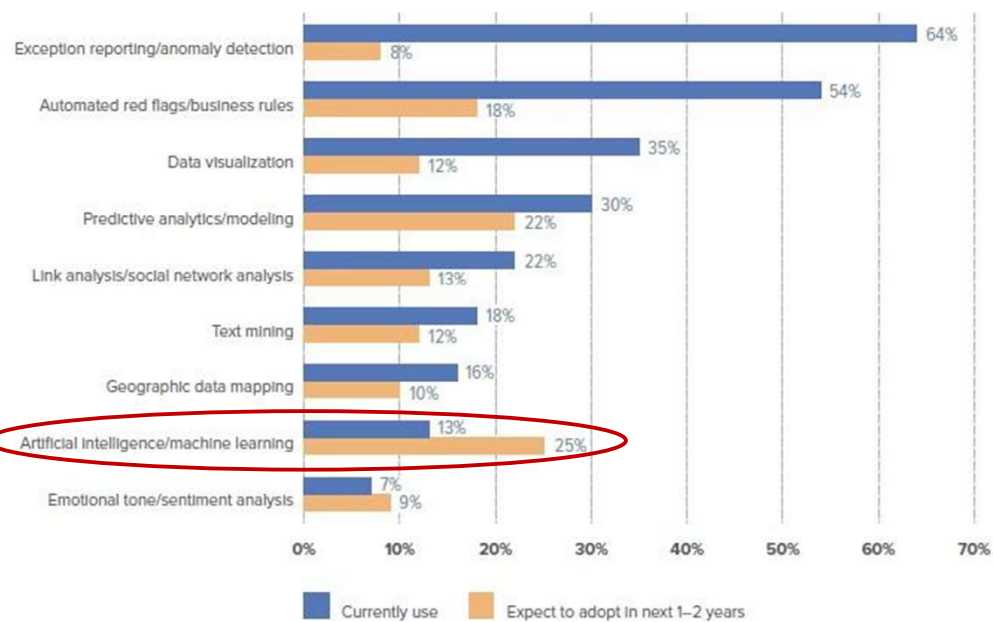
Error

Unintentional fault



9

FIG. 1 What data analysis techniques do organizations use to fight fraud?



<https://www.forbes.com/sites/louiscolombus/2019/08/01/ai-is-predicting-the-future-of-online-fraud-detection/#1a19bfa374f5>

10

10 seconds Polling Question - 1

Which of the following popular fraud costing the most?

- Credit card Fraud
- Healthcare Fraud
- Identity Fraud



11

• Credit card fraud: \$24.71 billion in 2016

• Healthcare fraud: \$68 billion per year

• Identity Fraud: 1.7 billion

<https://www.bcbcm.com/health-care-fraud/fraud-statistics.html>
<https://losspreventionmedia.com/credit-card-fraud-news-2018-update/>
<https://www.javelinstrategy.com/coverage-area/2019-identity-fraud-report-fraudsters-look-for-new-targets-and-victims-bear-brunt>

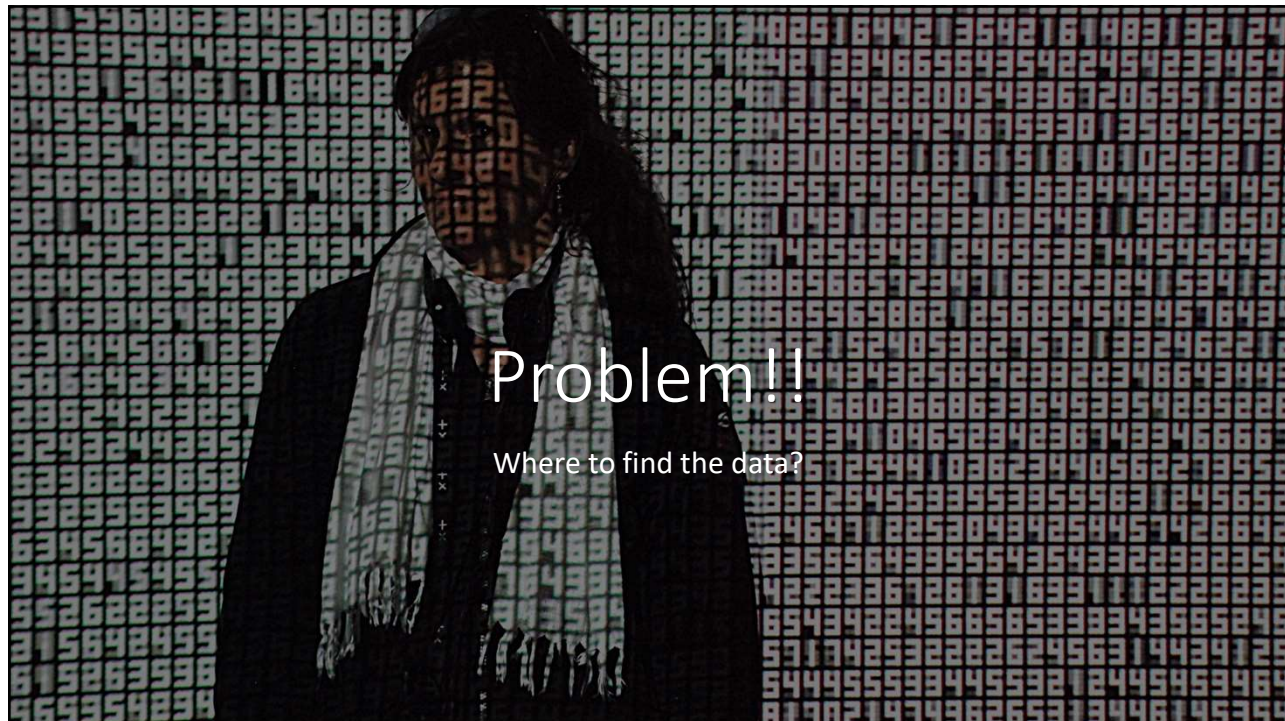
12

The screenshot shows the HHS.gov website with the following elements:

- Navigation:** About HHS, Programs & Services, Grants & Contracts, Laws & Regulations.
- Page Title:** HHS FY 2018 Budget in Brief - CMS - Overview
- Table of Contents:**
 - Current Law (1)
 - Medicare (2)
 - Medicaid
 - CHIP
 - State Grants and Demonstrations
 - Other Health Insurance Programs
 - Center for Medicare and Medicaid Innovation
 - Total Net Outlays, Current Law (3)
- Article:** Medicare Funds Totaling \$60 Billion Improperly Paid, Report Finds. By JIM AVILA, SERENA MARSHALL AND GITIKA KAUL. Jul 23, 2015, 5:59 PM ET.
- Video:** A video player for the article with a play button and a thumbnail showing a man speaking with a 'YOUR MONEY' graphic.
- Table:** World Countries by GDP table with columns: Rank, Name, GDP (IMF '19), GDP (UN '16), GDP Per Capita, 2019 Population.

> \$1 Trillion

13



14

Medicare Provider Utilization and Payment Data: Physician and Other Supplier

The screenshot shows the CMS.gov website with the following content:

- Header: CMS.gov, Centers for Medicare & Medicaid Services
- Navigation: Home | About CMS | Newsroom | Archive | Share | Help | Print
- Search: type search term here
- Menu: Medicare, Medicaid/CHIP, Medicare-Medicaid Coordination, Private Insurance, Innovation Center, Regulations & Guidance, Research, Statistics, Data & Systems, Outreach & Education
- Breadcrumbs: Home > Research, Statistics, Data and Systems > Medicare Provider Utilization and Payment Data > Medicare Provider Utilization and Payment Data: Physician and Other Supplier
- Section: Medicare Provider Utilization and Payment Data: Physician and Other Supplier
- Text: The Physician and Other Supplier Public Use File (Physician and Other Supplier PUF) provides information on services and procedures provided to Medicare beneficiaries by physicians and other healthcare professionals. The Physician and Other Supplier PUF contains information on utilization, payment (allowed amount and Medicare payment), and submitted charges organized by National Provider Identifier (NPI), Healthcare Common Procedure Coding System (HCPCS) code, and place of service. This PUF is based on information from CMS administrative claims data for Medicare beneficiaries enrolled in the fee-for-service program. The data in the Physician and Other Supplier PUF covers calendar years 2012 through 2017 and contains 100% final-action physician/supplier Part B non-institutional line items for the Medicare fee-for-service population.
- Text: While the Physician and Other Supplier PUF has a wealth of information on payment and utilization for Medicare Part B services, the dataset has a number of limitations. Of particular importance is the fact that the data may not be representative of a physician's entire practice as it only includes information on Medicare fee-for-service beneficiaries. In addition, the data are not intended to indicate the quality of care provided and are not risk-adjusted to account for differences in underlying severity of disease of patient populations. For additional limitations, please review the methodology document available below.
- Links: Medicare Physician and Other Supplier Data CY 2017, Medicare Physician and Other Supplier Data CY 2016, Medicare Physician and Other Supplier Data CY 2015, Medicare Physician and Other Supplier Data CY 2014, Medicare Physician and Other Supplier Data CY 2013, Medicare Physician and Other Supplier Data CY 2012
- Text: Inquiries regarding this data can be sent to MedicareProviderData@cms.hhs.gov.
- Text: To receive email notifications, please sign up for the Medicare Provider Data GovDelivery subscription here.
- Section: Downloads
 - Medicare Physician and Other Supplier PUF Methodology (PDF, 357KB)
 - Medicare Physician and Other Supplier PUF Frequently Asked Questions (PDF, 135KB)
- Page last Modified: 07/12/2019 10:23 AM

15

2012	2013	2014	2015	2016	2017
## NPI	## NPI	## npi	## npi	## NPI	## npi
## NPPES_PROVIDER_LAST_ORG_NAME	## NPPES_PROVIDER_LAST_ORG_NAME	## nppes_provider_last_org_name	## nppes_provider_last_org_name	## NPPES_PROVIDER_LAST_ORG_NAME	## nppes_provider_last_org_name
## NPPES_PROVIDER_FIRST_NAME	## NPPES_PROVIDER_FIRST_NAME	## nppes_provider_first_name	## nppes_provider_first_name	## NPPES_PROVIDER_FIRST_NAME	## nppes_provider_first_name
## NPPES_PROVIDER_MI	## NPPES_PROVIDER_MI	## nppes_provider_mi	## nppes_provider_mi	## NPPES_PROVIDER_MI	## nppes_provider_mi
## NPPES_CREDENTIALS	## NPPES_CREDENTIALS	## nppes_credentials	## nppes_credentials	## NPPES_CREDENTIALS	## nppes_credentials
## NPPES_PROVIDER_GENDER	## NPPES_PROVIDER_GENDER	## nppes_provider_gender	## nppes_provider_gender	## NPPES_PROVIDER_GENDER	## nppes_provider_gender
## NPPES_ENTITY_CODE	## NPPES_ENTITY_CODE	## nppes_entity_code	## nppes_entity_code	## NPPES_ENTITY_CODE	## nppes_entity_code
## NPPES_PROVIDER_STREET1	## NPPES_PROVIDER_STREET1	## nppes_provider_street1	## nppes_provider_street1	## NPPES_PROVIDER_STREET1	## nppes_provider_street1
## NPPES_PROVIDER_STREET2	## NPPES_PROVIDER_STREET2	## nppes_provider_street2	## nppes_provider_street2	## NPPES_PROVIDER_STREET2	## nppes_provider_street2
## NPPES_PROVIDER_CITY	## NPPES_PROVIDER_CITY	## nppes_provider_city	## nppes_provider_city	## NPPES_PROVIDER_CITY	## nppes_provider_city
## NPPES_PROVIDER_ZIP	## NPPES_PROVIDER_ZIP	## nppes_provider_zip	## nppes_provider_zip	## NPPES_PROVIDER_ZIP	## nppes_provider_zip
## NPPES_PROVIDER_STATE	## NPPES_PROVIDER_STATE	## nppes_provider_state	## nppes_provider_state	## NPPES_PROVIDER_STATE	## nppes_provider_state
## NPPES_PROVIDER_COUNTRY	## NPPES_PROVIDER_COUNTRY	## nppes_provider_country	## nppes_provider_country	## NPPES_PROVIDER_COUNTRY	## nppes_provider_country
## PROVIDER_TYPE	## PROVIDER_TYPE	## provider_type	## provider_type	## PROVIDER_TYPE	## nppes_provider_type
## MEDICARE_PARTICIPATION_INDICATOR	## MEDICARE_PARTICIPATION_INDICATOR	## medicare_participation_indicator	## medicare_participation_indicator	## MEDICARE_PARTICIPATION_INDICATOR	## medicare_participation_indicator
## PLACE_OF_SERVICE	## PLACE_OF_SERVICE	## place_of_service	## place_of_service	## PLACE_OF_SERVICE	## place_of_service
## HCPCS_CODE	## HCPCS_CODE	## hcpcs_code	## hcpcs_code	## HCPCS_CODE	## hcpcs_code
## HCPCS_DESCRIPTION	## HCPCS_DESCRIPTION	## hcpcs_description	## hcpcs_description	## HCPCS_DESCRIPTION	## hcpcs_description
## HCPCS_DRUG_INDICATOR	## HCPCS_DRUG_INDICATOR	## hcpcs_drug_indicator	## hcpcs_drug_indicator	## HCPCS_DRUG_INDICATOR	## hcpcs_drug_indicator
## LINE_SRVC_CNT	## LINE_SRVC_CNT	## line_srvc_cnt	## line_srvc_cnt	## LINE_SRVC_CNT	## line_srvc_cnt
## BENE_UNIQUE_CNT	## BENE_UNIQUE_CNT	## bene_unique_cnt	## bene_unique_cnt	## BENE_UNIQUE_CNT	## bene_unique_cnt
## BENE_DAY_SRVC_CNT	## BENE_DAY_SRVC_CNT	## bene_day_srvc_cnt	## bene_day_srvc_cnt	## BENE_DAY_SRVC_CNT	## bene_day_srvc_cnt
## AVERAGE_Medicare_ALLOWED_AMT	## AVERAGE_Medicare_ALLOWED_AMT	## average_Medicare_allowed_amt	## average_Medicare_allowed_amt	## AVERAGE_Medicare_ALLOWED_AMT	## average_Medicare_allowed_amt
## STDEV_Medicare_ALLOWED_AMT	## STDEV_Medicare_ALLOWED_AMT	## stdev_Medicare_allowed_amt	## stdev_Medicare_allowed_amt	## STDEV_Medicare_ALLOWED_AMT	## stdev_Medicare_allowed_amt
## AVERAGE_SUBMITTED_CHRG_AMT	## AVERAGE_SUBMITTED_CHRG_AMT	## average_submitted_chrg_amt	## average_submitted_chrg_amt	## AVERAGE_SUBMITTED_CHRG_AMT	## average_submitted_chrg_amt
## AVERAGE_Medicare_PAYMENT_AMT	## AVERAGE_Medicare_PAYMENT_AMT	## average_Medicare_payment_amt	## average_Medicare_payment_amt	## AVERAGE_Medicare_PAYMENT_AMT	## average_Medicare_payment_amt
## STDEV_Medicare_PAYMENT_AMT	## STDEV_Medicare_PAYMENT_AMT	## stdev_Medicare_payment_amt	## stdev_Medicare_payment_amt	## STDEV_Medicare_PAYMENT_AMT	## stdev_Medicare_payment_amt
## AVERAGE_Medicare_STANDARD_AMT	## AVERAGE_Medicare_STANDARD_AMT	## average_Medicare_standard_amt	## average_Medicare_standard_amt	## AVERAGE_Medicare_STANDARD_AMT	## average_Medicare_standard_amt
## STDEV_Medicare_STANDARD_AMT	## STDEV_Medicare_STANDARD_AMT	## stdev_Medicare_standard_amt	## stdev_Medicare_standard_amt	## STDEV_Medicare_STANDARD_AMT	## stdev_Medicare_standard_amt

16

This file is not yet accessible. A 508 compliant document will be posted as soon as it is available.

List of Excluded Individuals and Entities (LEIE)

The screenshot shows the OIG Exclusions Program website. The main heading is "List of Excluded Individuals and Entities (LEIE)". The website layout includes a navigation menu with links for About OIG, Reports, Fraud, Compliance, Exclusions, Newsroom, and Careers. The "LEIE Downloadable Databases" section is highlighted, showing a last update of 10-08-2020. Other sections include "Exclusions Program", "Monthly Supplement Archive", "Quick Tips", "Waivers", "Background Information", "Applying for Reinstatement", "Contact the Exclusions Program", "Frequently Asked Questions", "Special Advisory Bulletin and Other Guidance", "Exclusion Authorities", and "Working with Federal and State Partners".

17

RBC LASTNAME

RBC FIRSTNAME

RBC MIDNAME

RBC BUSNAME

RBC GENERAL

RBC SPECIALTY

RBC UPIN

RBC NPI

RBC DOB

RBC ADDRESS

RBC CITY

RBC STATE

RBC ZIP

RBC EXCLTYPE

RBC EXCLDATE

RBC REINDATE

RBC WAIVERDATE

RBC WVRSTATE

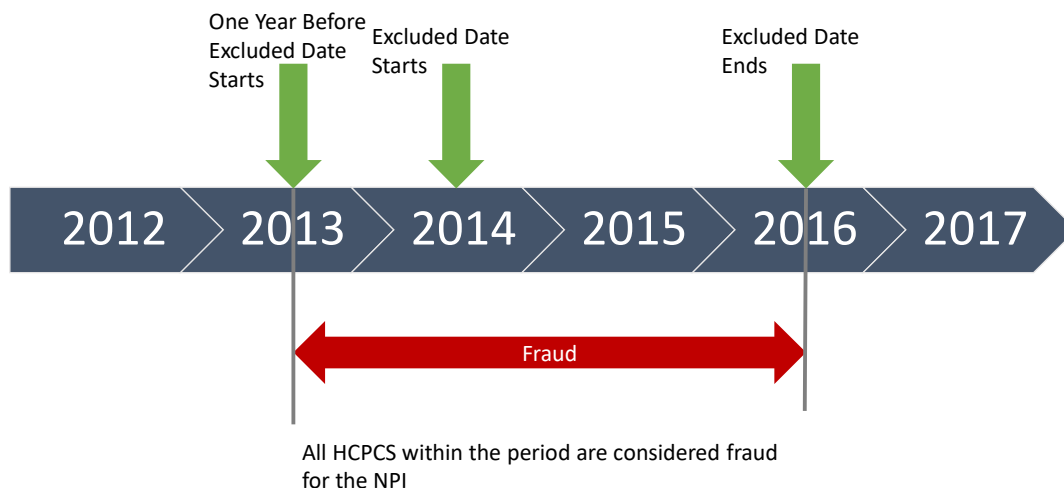
Mandatory Exclusions

Social Security Act	42 USC §	Amendment
1128(a)(1)	1320a-7(a)(1)	Conviction of program-related crimes. Minimum Period: 5 years
1128(a)(2)	1320a-7(a)(2)	Conviction relating to patient abuse or neglect. Minimum Period: 5 years
1128(a)(3)	1320a-7(a)(3)	Felony conviction relating to health care fraud. Minimum Period: 5 years
1128(a)(4)	1320a-7(a)(4)	Felony conviction relating to controlled substance. Minimum Period: 5 years
1128(c)(3)(G)(i)	1320a-7(c)(3)(G)(i)	Conviction of second mandatory exclusion offense. Minimum Period: 10 years
1128(c)(3)(G)(ii)	1320a-7(c)(3)(G)(ii)	Conviction of third or more mandatory exclusion offenses. Permanent Exclusion

<https://oig.hhs.gov/exclusions/authorities.asp>

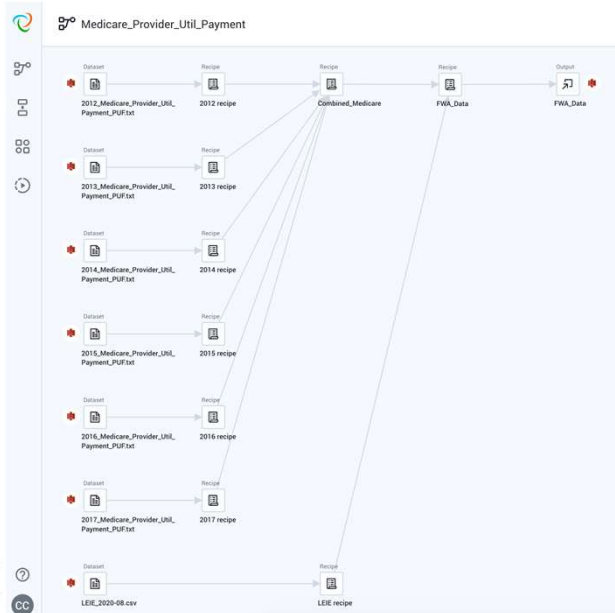
18

Define what is fraud based on the data set



19

Overall data ingestion flow



20

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Final data set structure

RBC	provider_type	Provider's specialty, e.g. Internal Medicine, Dermatology
👤	nppes_provider_gender	Provider Gender
RBC	hcpcs_code	Procedure or Service performed by the provider
#	line_srvc_cnt	Number of procedures or services the provider performed
#	bene_unique_cnt	Number of distinct Medicare beneficiaries receiving the service/procedure
#	bene_day_srvc_cnt	Number of distinct Medicare beneficiaries per day by the provider
##	average_submitted_chrg_amt	Average charge the provider submitted for the service or procedure
##	average_medicare_payment_amt	Average payment made to a provider per claim for the service
🕒	fraud	Fraud label based on the logic described before



21

Let's predict using Machine Learning!

Based on my rich experience in AI 😎, I can build a model guaranteed with 99.9% accuracy within 10 seconds!

EVERYTHING
Is NOT Fraud



22

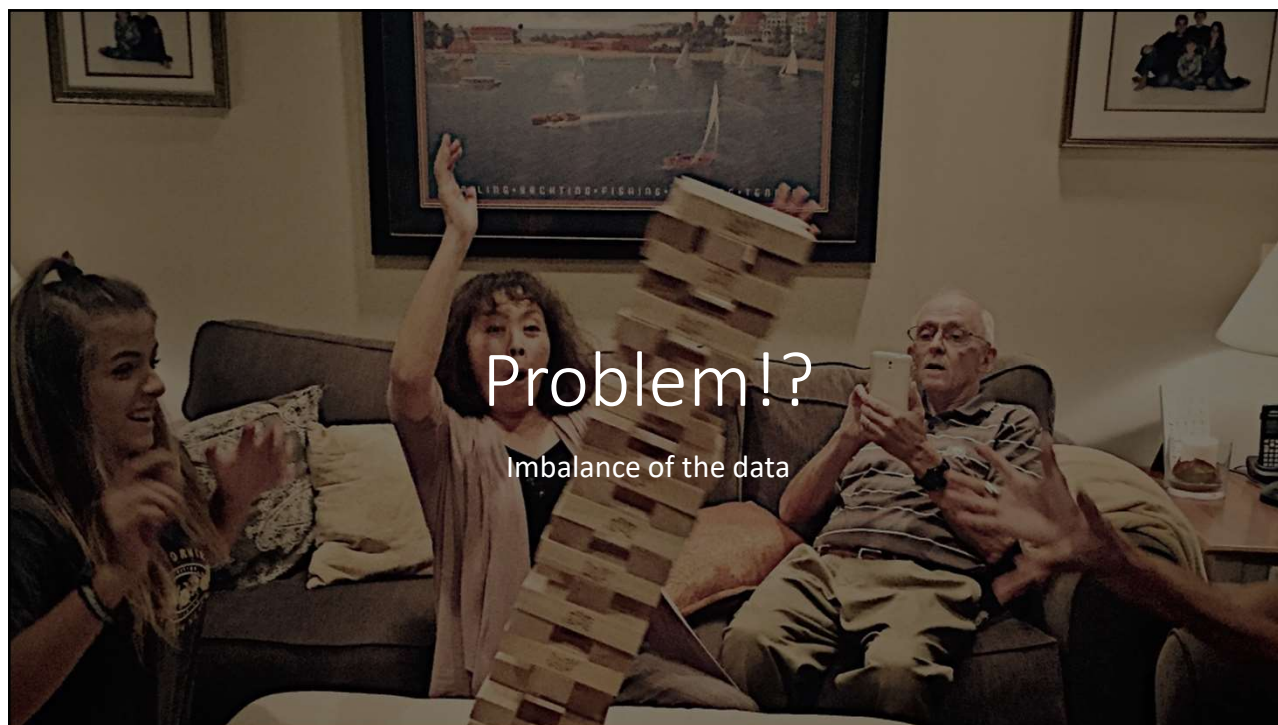
Confusion Matrix

- Total: 54,337,938
- Normal: 54,333,245
- Fraud: 4,693 (0.0086%)

		Predicted Class		
		Positive	Negative	
Actual Class	Positive	True Positive (TP)	False Positive (FN)	Sensitivity/Recall $\frac{TP}{TP + FN}$
	Negative	False Negative (FP)	True Negative (TN)	Specificity $\frac{TN}{TN + FP}$
		Precision $\frac{TP}{TP + FP}$	Negative Predictive Value $\frac{TN}{TN + FN}$	Accuracy $\frac{TP + TN}{TP + TN + FP + FN}$



23



24

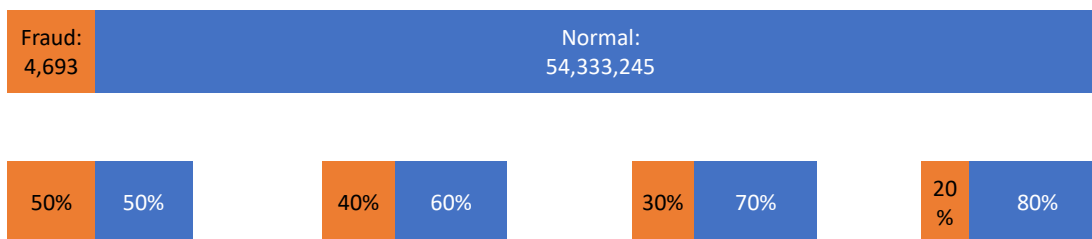


25



26

Random Under Sampling (RUS)



27

```
1 import tensorflow as tf
2 CATEGORICAL_COLUMNS = ['appes_provider_gender', 'provider_type', 'hpcs_code']
3 INT_COLUMNS = ['time_serve_cnt', 'home_unique_cnt', 'home_dsp_serve_cnt']
4 FLOAT_COLUMNS = ['average_submitted_chrg_amt', 'average_medicare_payment_amt']
5
6
7 feature_columns = []
8 for feature_name in CATEGORICAL_COLUMNS:
9     vocabulary = tf.train.FeatureNameVocabulary.from_instances(feature_name)
10    feature_columns.append(tf.feature_column.categorical_column_with_vocabulary_list(feature_name, vocabulary))
11
12 for feature_name in FLOAT_COLUMNS:
13    feature_columns.append(tf.feature_column.numeric_column(feature_name, dtype=tf.float32))
14
15 for feature_name in INT_COLUMNS:
16    feature_columns.append(tf.feature_column.numeric_column(feature_name, dtype=tf.int16))
17
18 # Use entire batch since this is such a small dataset.
19 NUM_EXAMPLES = len(y_train)
20
21 def make_input_fn(X, y, n_epochs=None, shuffle=True):
22     def input_fn():
23         dataset = tf.data.Dataset.from_tensor_slices((dict(X), y))
24         if shuffle:
25             dataset = dataset.shuffle(NUM_EXAMPLES)
26         # For training, cycle thru dataset as many times as need (n_epochs=None).
27         dataset = dataset.repeat(n_epochs)
28         # In memory training doesn't use batching.
29         dataset = dataset.batch(NUM_EXAMPLES)
30         return dataset
31     return input_fn
32
33 # Training and evaluation input functions.
34 train_input_fn = make_input_fn(dict(train), y_train)
35 eval_input_fn = make_input_fn(dict(eval), y_eval, shuffle=False, n_epochs=1)
36
37 n_batches = 1
38 est = tf.estimator.BoostedTreesClassifier(feature_columns,
39                                         n_batches_per_layer=n_batches)
40
41 # The model will stop training once the specified number of trees is built, not
42 # based on the number of steps.
43 est.train(train_input_fn, max_steps=100)
44
45 # Eval.
46 result = est.evaluate(eval_input_fn)
47 clear_output()
48 print(pd.Series(result))
```

Using 50:50 Class Distribution

TensorFlow Boosted Tree Classifier

Accuracy: 0.760789

Precision: 0.706313

Recall: 0.857778

AUC: 0.845611



28

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Potential Improvement


- Add back Geographical information to the data set in analysis
- Add beneficiary data to form a graph analysis. Right now we only analyze from Provide side
- More granular e.g. by type
- Add more metrics (Medicare Standard Amount, Medicare Allowed Amount)
- A lot of missing NPI in LEIE. looking up missing NPI numbers in the National Plan and Provider Enumeration System (NPPES) registry



Even with those improvements, there are still limitations

- Tagged data not always be available
- Not good for emerging anomalies with entirely new and more sophisticated forms



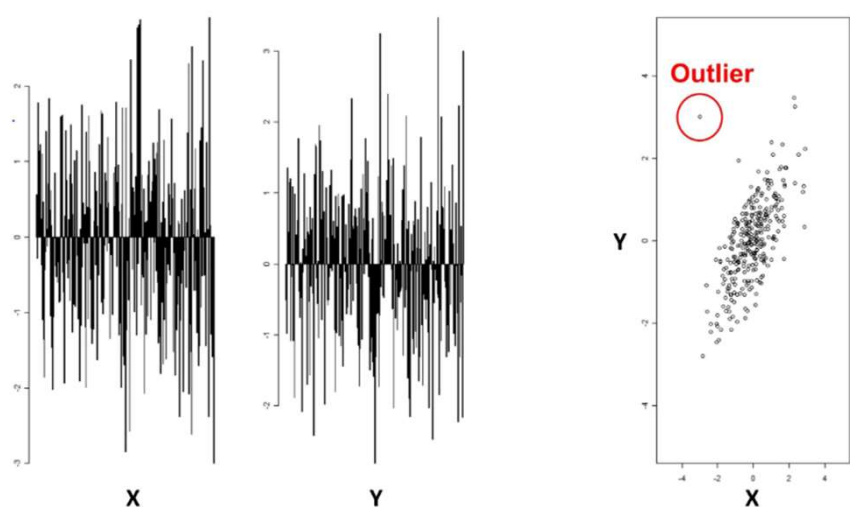


Unsupervised Learning


- Good for detecting Outlier, but it doesn't mean that is Fraud.
- It provides hint to start finding Fraud.

31

Where is the Outlier?



The figure consists of three plots. On the left, two line graphs labeled 'X' and 'Y' show highly volatile, noisy data points fluctuating around a zero baseline. On the right, a scatter plot shows a positive correlation between X and Y, with a single data point at the top-left corner circled in red and labeled 'Outlier'.

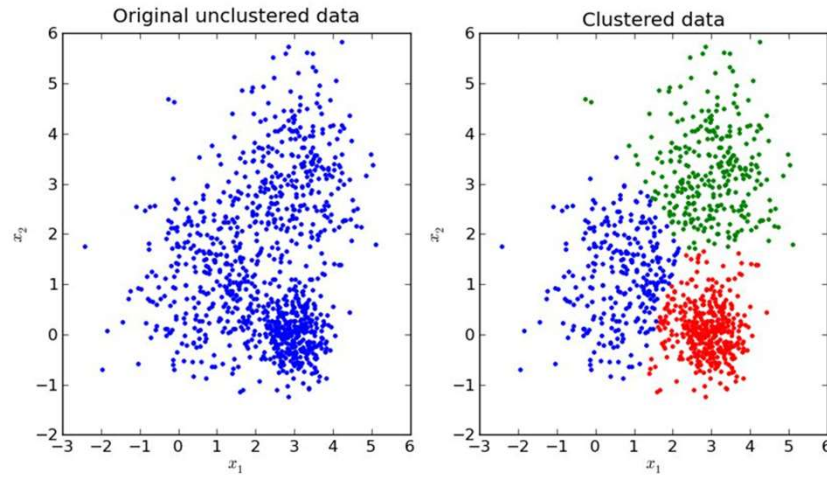


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https://miro.medium.com/max/1944/1*Ba0iTGWAoFi-3-E-rjGdg.jpeg

32

Unsupervised Clustering



CCSQ WORLD USABILITY DAY 33

<http://www.frankichamaki.com/data-driven-market-segmentation-more-effective-marketing-to-segments-using-ai/>

33



<https://www.youtube.com/watch?v=BmcaD1j0y8I>

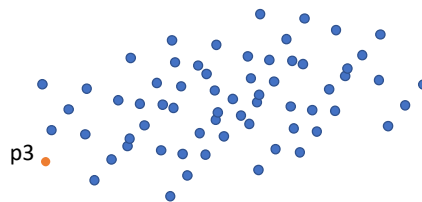
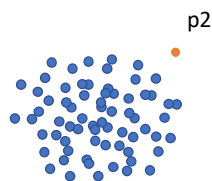
34

This file is not yet accessible. A 508 compliant document will be posted as soon as it is available.

10 seconds Polling Question: Which point is considered outlier?

Nearest Neighbor Approach

- By distance
- Having the largest distance away from closest points
- Only p1 is considered outlier



Density based Approach

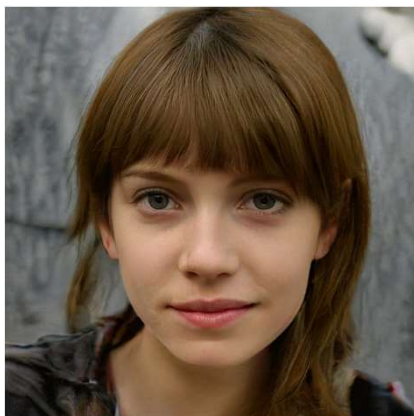
- By density
- Having the lowest density among closest points
- Both p1 and p2 are considered outlier



35

10 seconds Polling Question -3

You must know her for this 3rd approach

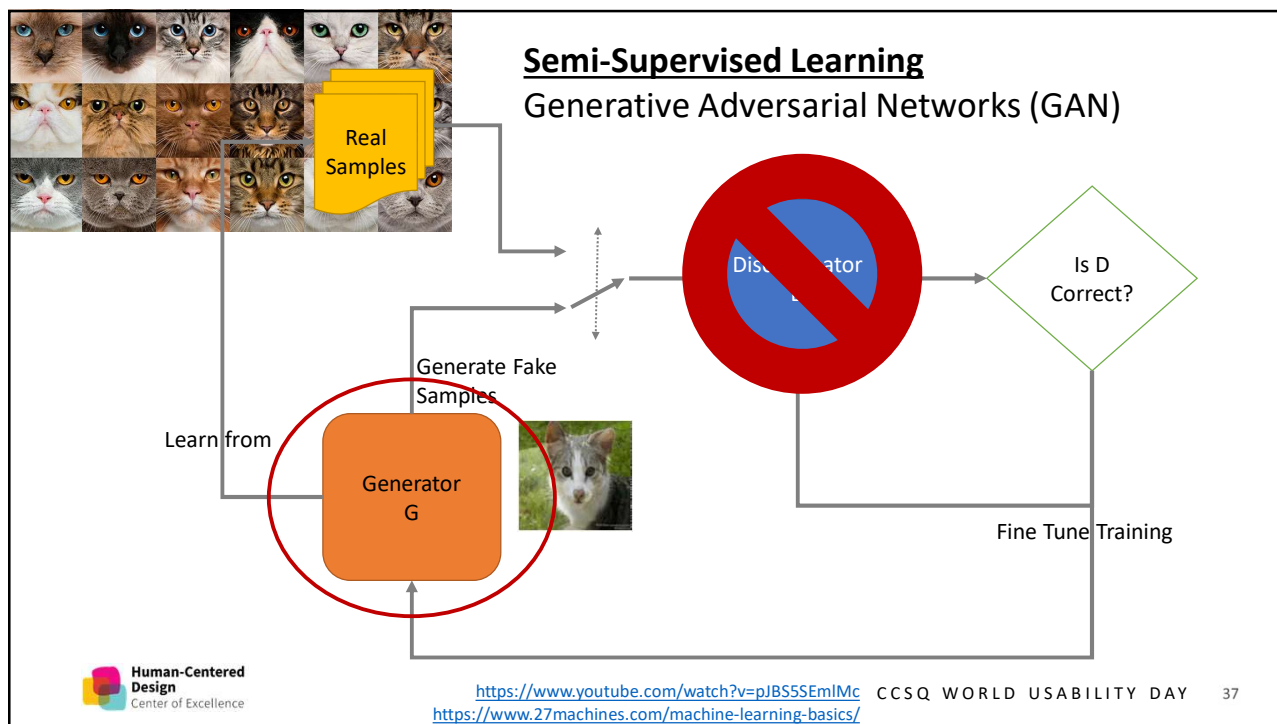


Who is she?

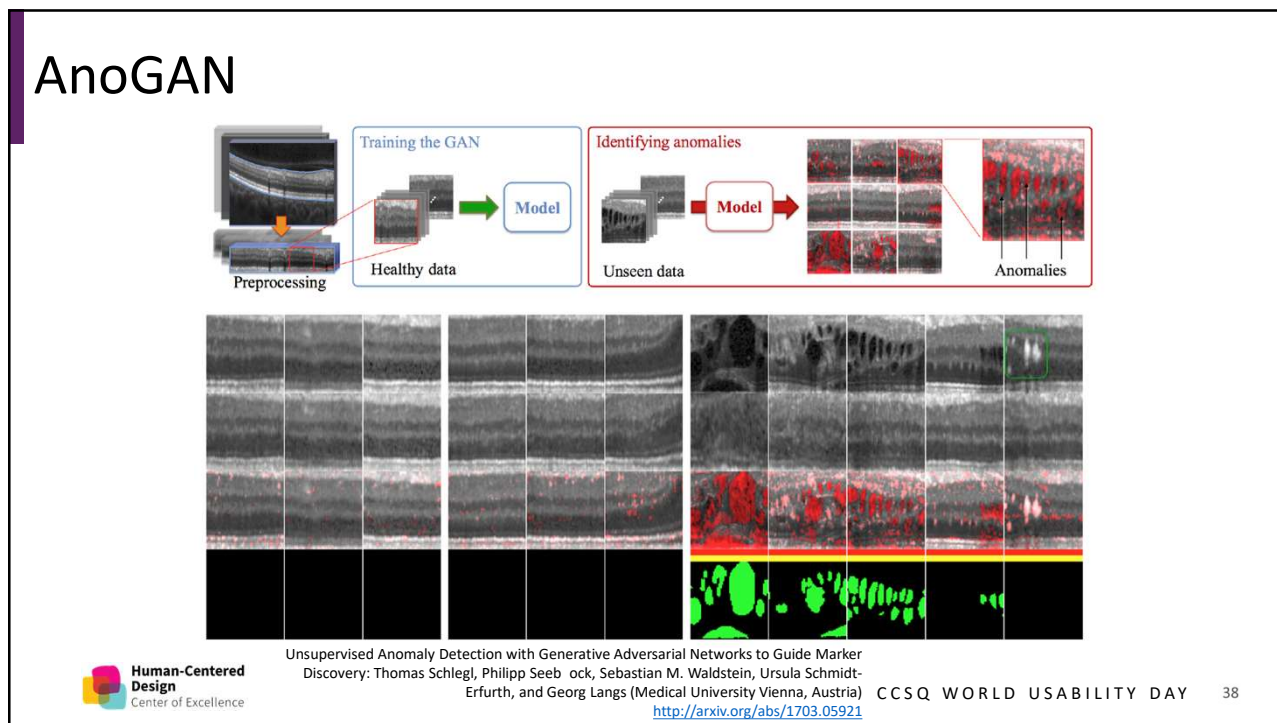
- She committed a \$100M fraud in a European bank last year by guessing the admin password using AI algorithm
- She is an actually a man dressed in disguise to fool the airport security smuggling 500 fake passports (with valid passport numbers produced by AI) in US last year
- The person inventing this 3rd approach AI algorithm

<http://stylegan.xyz/paper>
<https://github.com/NVLabs/stylegan>

36



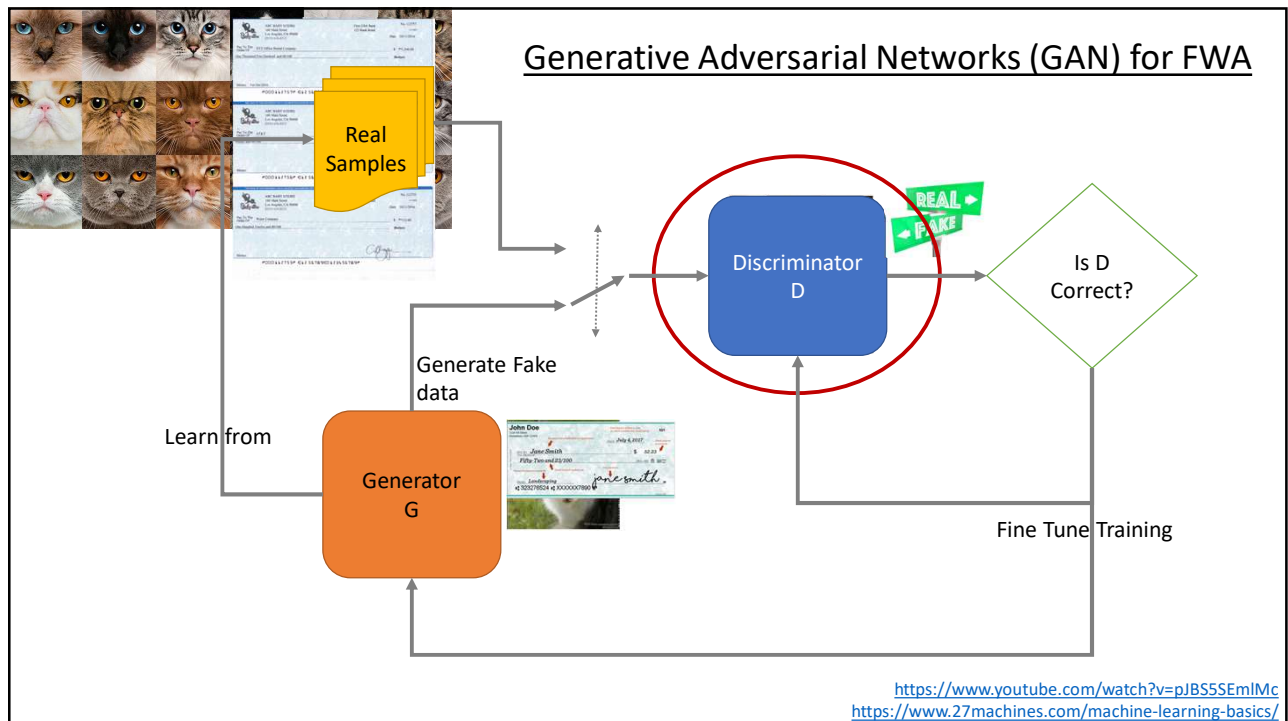
37



38

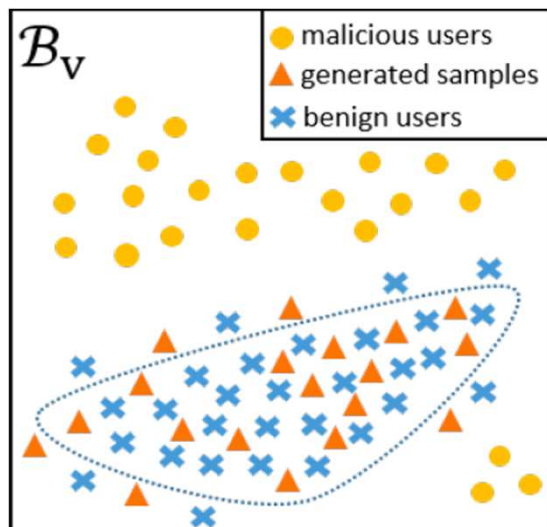


39



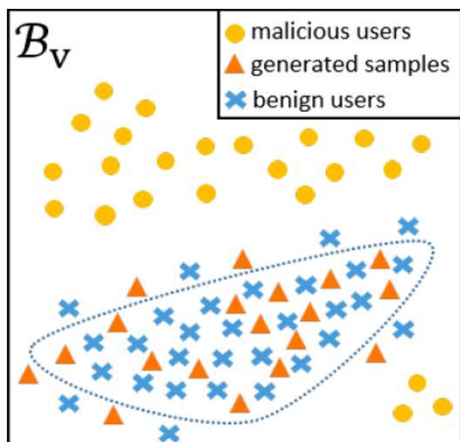
40

Traditional GAN

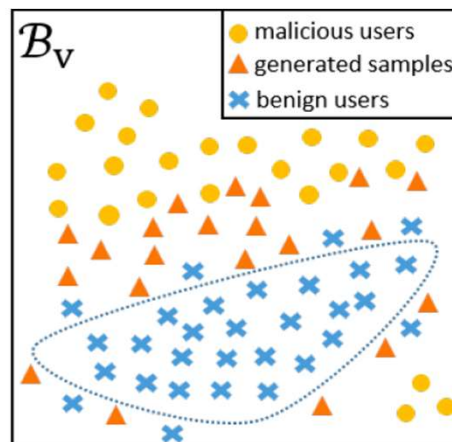


41

One-Class Adversarial Nets (OCAN) GAN



(a) Regular GAN



(b) Complementary GAN

42

Advantage of One-Class Adversarial Nets

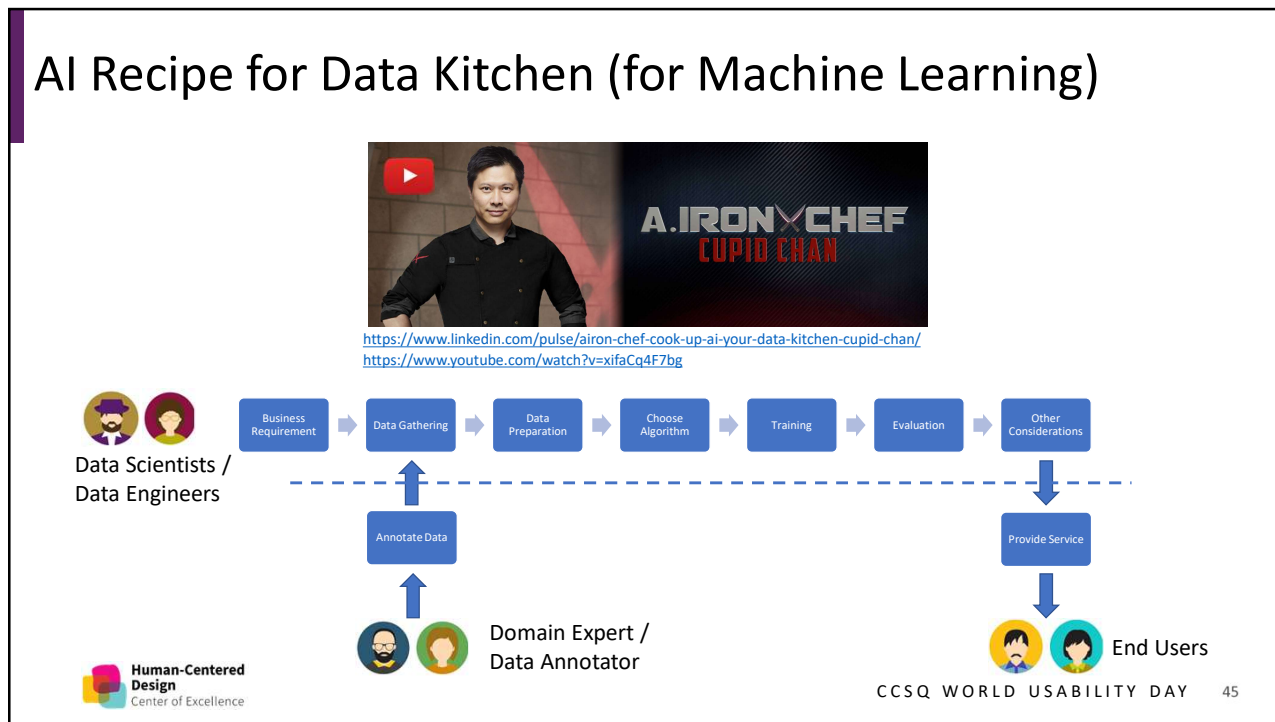
- No need for fraud data
 - No need to manually prepare a mixed training data set, which is usually has a very few fraud data to start with
- Discriminator will take in either real benign or generated malicious
 - More adaptive to different kinds of malicious behavior
- Adapt to newly emerged normal user pattern

43

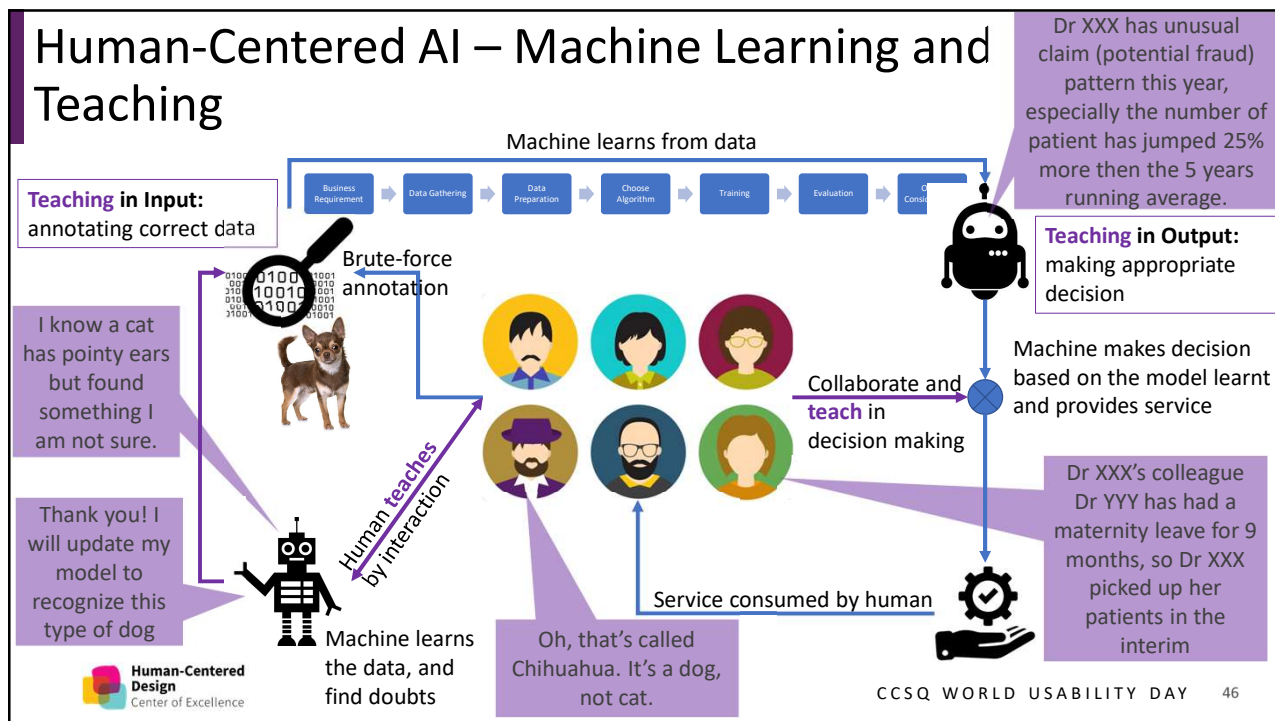
Recap: What we have talked about so far...



44



45



46

MEDICARE PAYMENT AMOUNT FRAUD ANALYSIS

Fraud KPIs

- Fraud Count: 363
- Line Service Count: 45,088,084
- Bene Day Service Count: 38,352,132
- Bene Unique Count: 22,430,803
- Avg. Submitted Charge Amount: \$171.12
- Avg. Medicare Payment Amount: \$49.01

Medicare Reimbursement Details

Line Item	Provider Type	HCPES Provider Gender	HCPES Code	Fraud?	Confirm or Reject	Commentary	Comment Timestamp	Line Service Count	Bene Unique Count	Bene Day Service Count	Avg. Medicare Payment Amount	Avg. Submitted Charge Amount
1118	Family Practice	F	99214	TRUE	Rejected	Further investigation shows that one doctor left the office sick and a fellow doctor covered those established patients.	11/9/2020 2:15:46 PM	47	18	47	\$61.92	\$156.00
15631	Family Practice	M	99214	TRUE	Confirmed		11/9/2020 3:15:58 PM	25	21	25	\$40.89	\$131.00
160863	Family Practice	F	99214	TRUE	Confirmed		11/9/2020 3:15:58 PM	47	18	47	\$61.92	\$156.00
165503	Family Practice	M	99214	TRUE	Confirmed		11/9/2020 3:15:58 PM	25	21	25	\$40.89	\$131.00
189133	Infectious Disease	M	99214	TRUE	Confirmed	This is correctly attributed as fraud. This doctor was billing as if these were new patients, not regular patients as per this HCPES code.	11/9/2020 3:15:58 PM	38	22	38	\$89.47	\$125.52
205403	General Practice	M	99214	TRUE	Confirmed		11/9/2020 3:15:58 PM	58	50	58	\$57.23	\$188.00
8	Family Practice	M	99214	FALSE	Confirmed		11/9/2020 3:15:58 PM	226	115	226	\$74.78	\$217.00
9	Family Practice	M	99214	FALSE	Confirmed		11/9/2020 3:15:58 PM	226	115	226	\$74.78	\$217.00
21	Family Practice	M	99214	FALSE	Confirmed	Human intervention has confirmed that the AI model has correctly predicted there is no fraud within the last year.	11/9/2020 3:11:02 PM	348	166	348	\$78.17	\$221.64
34	Family Practice	M	99214	FALSE	Confirmed		11/9/2020 3:11:02 PM	250	125	250	\$75.75	\$225.50
63	Family Practice	M	99214	FALSE	Confirmed		11/9/2020 3:11:02 PM	181	100	181	\$78.70	\$204.78

Confirm/Reject Fraud:

Line Item Search: 15631

Confirm/Reject: Confirm

Add Justification: Other evidences also support that the provider committed fraud

Submit

Latest Updates to Fraud Prediction Model

Comment Timestamp	Line Item	Commentary	Confirm or Reject
11/9/2020 10:52:52 PM	265380	Further investigation shows that one doctor left the office sick and a fellow doctor covered those established patients.	Rejected
11/9/2020 3:15:58 PM	189133	This is correctly attributed as fraud. This doctor was billing as if these were new patients, not regular patients as per this HCPES code.	Confirmed
11/9/2020 3:11:02 PM	21	Human intervention has confirmed that the AI model has correctly predicted there is no fraud within the last year.	Confirmed
11/9/2020 2:15:43 PM	11168	Further investigation shows that one doctor left the office sick and a fellow doctor covered those established patients.	Rejected
11/9/2020 2:14:48 AM	4	Recent evidence came to light that shows this doctor frequently submitted additional procedures. Updating model in order to train AI.	Rejected
11/9/2020 2:24:04 AM	1	We originally thought this doctor was overcharging, but we confirmed he was covering patients for practice partner.	Confirmed
11/9/2020 2:21:58 AM	11164	This family practice doctor was found to be charging more procedures than providing.	Confirmed

Center of Excellence

CCSQ WORLD USABILITY DAY 47

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When you talk about AI, think of IA!

Artificial Intelligence

In Speaker Packet: *There is zero tolerance for sales pitches masquerading as educational or informational.*

VS

Intelligence Augmentation

48

AI + BI = CI

AI (Artificial Intelligence) – Excellence in learning with speed

BI (Business Intelligence) – Historically proven to enable human intuited the direction

CI – (Cognitive Intelligence) - Intelligence by combining the Speed of how a Machine Learn and Direction Intuited from Human Insight



2017 CONFERENCE ON HEALTH IT AND ANALYTICS (CHITA)



November 3rd – 4th 2017 | Washington, DC
Presented by the Center for Health Information & Decision Systems

The Conference on Health IT and Analytics (previously known as the Workshop on Health IT & Economics) is an annual health IT and analytics research summit, including a doctoral consortium that each year gathers prominent scholars from more than 40 research institutes, and leading policy and practitioner attendees in a vibrant setting to discuss opportunities and challenges in the design, implementation and management of health information technology and analytics. Its goal is to deepen our understanding of strategy, policy and systems fostering health IT and analytics effective use and to stimulate new ideas with both policy and business implications.

This forum provides a productive venue to facilitate interaction and collaboration among academia, government, and industry. Now in its 8th year, each year CHITA draws over 100 participants.

Hosted by the Center for Health Information & Decision Systems (CHIDS), support for CHITA is provided by the Robert H. Smith School of Business and the University of Michigan School of Public Health.

We hope that you will join us for this engaging, stimulating and fun event!

FEATURED SPEAKERS



FEATURED PANELISTS



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... LinkedIn Story continues



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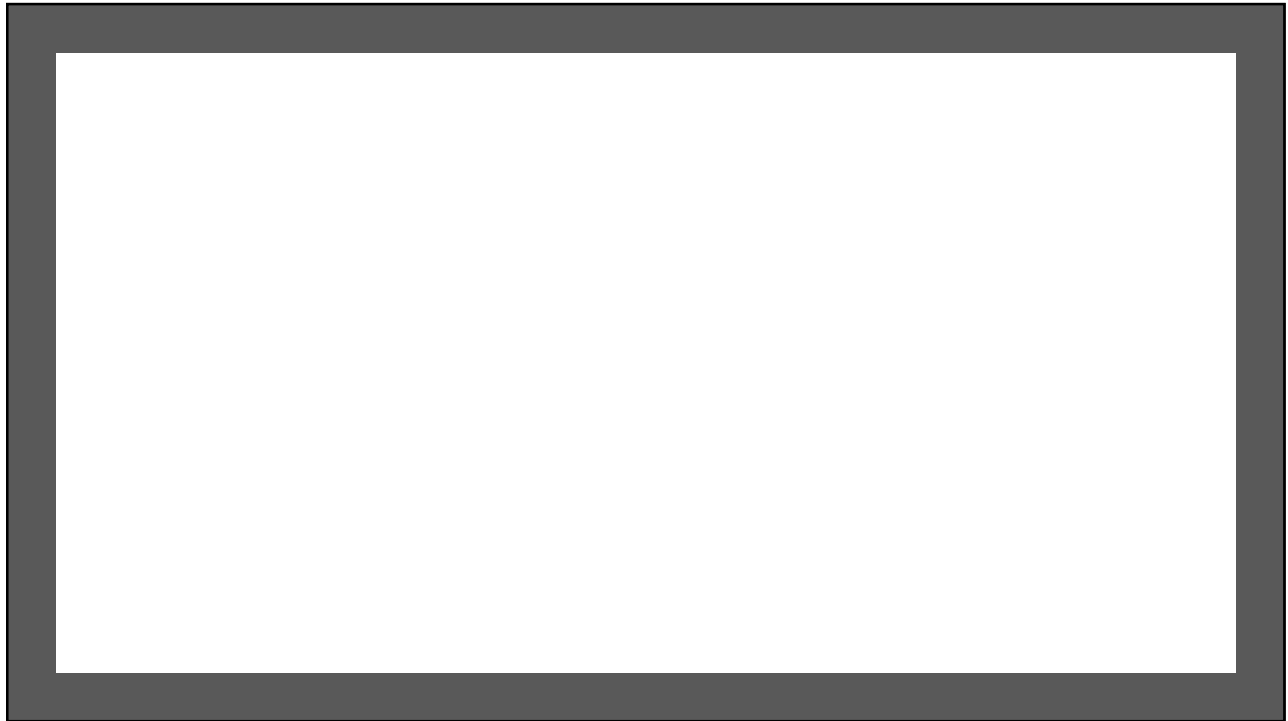
I decided to find my most knowledgeable friend for help

The screenshot shows a Google search for 'jacqueline mars'. The search results include a Wikipedia entry and a Forbes profile. The Wikipedia entry provides biographical information: 'Jacqueline Mars (born October 10, 1939) is an American heiress and investor. She is the daughter of Audrey Ruth (Meyer) and Forrest Mars, Sr., and granddaughter of Frank C. Mars, founders of the American candy company Mars, Incorporated. Education: Miss Hall's School Parent(s): Forrest Mars, Sr. (1904–1999); Audr... Born: October 10, 1939 (age 80) Relatives: Frank C. Mars (grandfather); Forrest... Career - Personal life'. The Forbes profile is titled 'Jacqueline Mars - Forbes' and states 'Jacqueline Mars owns an estimated one third of Mars, the world's largest candymaker, founded...'. The search interface includes navigation tabs for All, News, Images, Videos, Books, and More, along with a feedback button.

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The screenshot shows a text message conversation. Cupid Chan sends a message: 'I am sorry, but exactly what?'. Jacqueline Mars replies: 'What you do in your place of work and the profitable it is.'. Cupid Chan replies: 'i see'. Jacqueline Mars says: 'Cupid Chan is typing...'. Cupid Chan sends a typing indicator. Jacqueline Mars replies: 'Don't you want to talk to me about it's fine I'm sorry 😊'. Cupid Chan replies: 'Cupid Chan is a seasoned professional who is well-established in the industry. His journey started out as one of the key players in building a world-class BI platform. Aside from holding various technical accreditations, his credential extends into business'. Jacqueline Mars replies: 'WOW Cool'.

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How to ~~fight~~ **conduct**
Fraud, Waste
and Abuse using
Machine
Learning AND
Machine
Teaching?



Presented by
Cupid Chan
Anonymous Hacker

Vulnerability
WORLD ~~USABILITY~~ DAY




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Cupid Chan

- Board of Directors and Technical Steering Committee, Chairperson of BI & AI Project, Linux Foundation ODPI
- Senior Fellow & Adjunct Professor, University of Maryland College Park

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